

### Solution 1: Connection between MLE and ERM

(a) We can make use of the “substitution trick” from Exercise Sheet 1, i.e.,  $z^{(i)} = m(y^{(i)})$ . Then, it holds that  $z^{(i)} \mid \mathbf{x}$  is distributed as  $\mathcal{N}(m(f_{\text{true}}(\mathbf{x}^{(i)})), \sigma^2)$ , since  $z^{(i)} = m(f_{\text{true}}(\mathbf{x}^{(i)})) + \epsilon^{(i)}$  and  $\epsilon^{(i)} \sim \mathcal{N}(0, \sigma^2)$ . Note that  $(\mathbf{x}^{(1)}, z^{(1)}), \dots, (\mathbf{x}^{(n)}, z^{(n)})$  are iid, as transforming  $y^{(1)}, \dots, y^{(n)}$  via  $m$  to  $z^{(1)}, \dots, z^{(n)}$  preserves the stochastic independence property.

(b) The likelihood for  $(\mathbf{x}^{(1)}, z^{(1)}), \dots, (\mathbf{x}^{(n)}, z^{(n)})$  is

$$\begin{aligned} \mathcal{L}(\boldsymbol{\theta}) &= \prod_{i=1}^n p\left(z^{(i)} \mid f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}), \sigma^2\right) \\ &\propto \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n \left[z^{(i)} - m\left(f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})\right)\right]^2\right). \end{aligned}$$

So, the negative log-likelihood for  $(\mathbf{x}^{(1)}, z^{(1)}), \dots, (\mathbf{x}^{(n)}, z^{(n)})$  is

$$\begin{aligned} -\ell(\boldsymbol{\theta}) &= -\log(\mathcal{L}(\boldsymbol{\theta})) \\ &= -\log\left(\exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n \left[z^{(i)} - m\left(f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})\right)\right]^2\right)\right) \\ &\propto \sum_{i=1}^n \left[z^{(i)} - m\left(f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})\right)\right]^2 \\ &= \sum_{i=1}^n \left[m(y^{(i)}) - m\left(f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})\right)\right]^2. \end{aligned}$$

Thus, the negative log-likelihood for a parameter  $\boldsymbol{\theta}$  is proportional to the empirical risk of a hypothesis  $f(\cdot \mid \boldsymbol{\theta})$  w.r.t. the generalized L2-loss function of Exercise sheet 1, i.e.,  $L(y, f(\mathbf{x})) = (m(y) - m(f(\mathbf{x})))^2$ .

(c) First, we specify the feature space:  $\mathcal{X} = \{1\} \times \mathbb{R}$ , i.e., any feature  $\mathbf{x} \in \mathcal{X}$  is of the form  $\mathbf{x} = (x_1, x_2)^\top = (1, x_2)^\top$  for some  $x_2 \in \mathbb{R}$ . According to the exercise we use  $m(x) = \log(x)$ , whose inverse is  $m^{-1}(x) = \exp(x)$ . Let us rewrite Forbes’ conjectured model  $y = \theta_1 \exp(\theta_2 x + \epsilon)$  into  $y = m^{-1}(m(f(\mathbf{x} \mid \boldsymbol{\theta})) + \epsilon)$ , for some suitable hypothesis  $f(\mathbf{x} \mid \boldsymbol{\theta})$ :

$$\begin{aligned} y &= \theta_1 \exp(\theta_2 x + \epsilon) \\ &= \exp(\log(\theta_1 \exp(\theta_2 x + \epsilon))) \\ &= \exp(\log(\theta_1) + \theta_2 x + \epsilon) && \text{(Functional equation of exp)} \\ &= \exp(\log(\theta_1) + \log(\exp(\theta_2 x)) + \epsilon) \\ &= \underbrace{\exp}_{=m^{-1}}(\underbrace{\log}_{=m}(\theta_1 \exp(\theta_2 x)) + \epsilon) && \text{(Functional equation of log)} \\ &= m^{-1}(m(\theta_1 \exp(\theta_2 x)) + \epsilon). \end{aligned}$$

With this, we see that  $f(\mathbf{x} \mid \boldsymbol{\theta}) = \theta_1 x_1 \exp(\theta_2 x_2) = \theta_1 \exp(\theta_2 x_2)$  is a suitable functional form for the hypotheses. Thus, we use as our parameter space  $\Theta = \mathbb{R}_+ \times \mathbb{R}$  which gives rise to the hypothesis space

$$\mathcal{H} = \{f(\mathbf{x} \mid \boldsymbol{\theta}) = \theta_1 x_1 \exp(\theta_2 x_2) \mid \boldsymbol{\theta} \in \Theta\}.$$

**Alternative:** Note that we could alternatively rephrase the learning problem by applying the logarithm on both sides of Forbes’ model:

$$y = \theta_1 \exp(\theta_2 x + \epsilon) \quad \Leftrightarrow \quad \log(y) = \log(\theta_1) + \theta_2 x + \epsilon,$$

so that we work with the logarithm of the original labels, i.e., we consider  $z^{(1)} = \log(y^{(1)}), \dots, z^{(n)} = \log(y^{(n)})$  instead of  $y^{(1)}, \dots, y^{(n)}$ . A suitable hypothesis space is then

$$\mathcal{H} = \{f(\mathbf{x} \mid \boldsymbol{\theta}) = \log(\theta_1)x_1 + \theta_2x_2 \mid \boldsymbol{\theta} \in \Theta\},$$

which are the linear functions<sup>1</sup>  $\mathbf{x}^\top \boldsymbol{\theta}$  of features in  $\mathcal{X}$ . The empirical risk minimizer in this case is specified by the parameter

$$(\log(\hat{\theta}_1), \hat{\theta}_2)^\top = \hat{\boldsymbol{\theta}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{z}, \quad \mathbf{z} = (\log y^{(1)}, \dots, \log y^{(n)})^\top,$$

(see Chapter 02.02 of I2ML) which for this simple case is:

$$\hat{\theta}_2 = \frac{\sum_{i=1}^n (\mathbf{x}_2^{(i)} - \bar{\mathbf{x}}_2)(\log(y^{(i)}) - \overline{\log(y)})}{\sum_{i=1}^n (\mathbf{x}_2^{(i)} - \bar{\mathbf{x}}_2)^2},$$

$$\hat{\theta}_1 = \exp\left(\overline{\log(y)} - \hat{\theta}_2 \bar{\mathbf{x}}_2\right),$$

where  $\bar{\mathbf{x}}_2 = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_2^{(i)}$  and  $\overline{\log(y)} = \frac{1}{n} \sum_{i=1}^n \log(y^{(i)})$ .

```
#' @param X the feature input matrix X
#' @param y the outcome vector y
#' @param theta coefficient vector for the model (2-dimensional)

# Load MASS and data set forbes
library(MASS)
data(forbes)
attach(forbes)

# initialize the data set
X = cbind(rep(1,17),bp)
y = pres

#' function to represent your models via the parameter vector theta = c(theta_1, theta_2)
#' @return a predicted label y_hat for x
f <- function(x, theta){

  return((exp(theta[2]*x[2])*theta[1]*x[1]))

}

#' @return a vector consisting of the optimal parameter vector
optim_coeff <- function(X,y){

  #' @return the empirical risk of a parameter vector theta
  emp_risk <- function(theta){
    sum( (log(y) - log(apply(X,1,f,theta)))^2 )
  }

  return(
    optim(c(0.4,0.5),
          emp_risk,
          method = "L-BFGS-B",
          lower=c(0,-Inf),
          upper=c(Inf,Inf))$par)
  # note that c(0.4,0.5) can be replaced by any other theta vector
  # satisfying the constraint theta[1]>0
}
```

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<sup>1</sup>Note that  $\log(\theta_1)$  can be any value in  $\mathbb{R}$ .

```

# optimal coefficients
hat_theta = optim_coeff(X,y)
print(hat_theta)

## [1] 0.38050940 0.02059961

# Checking Forbes' model visually

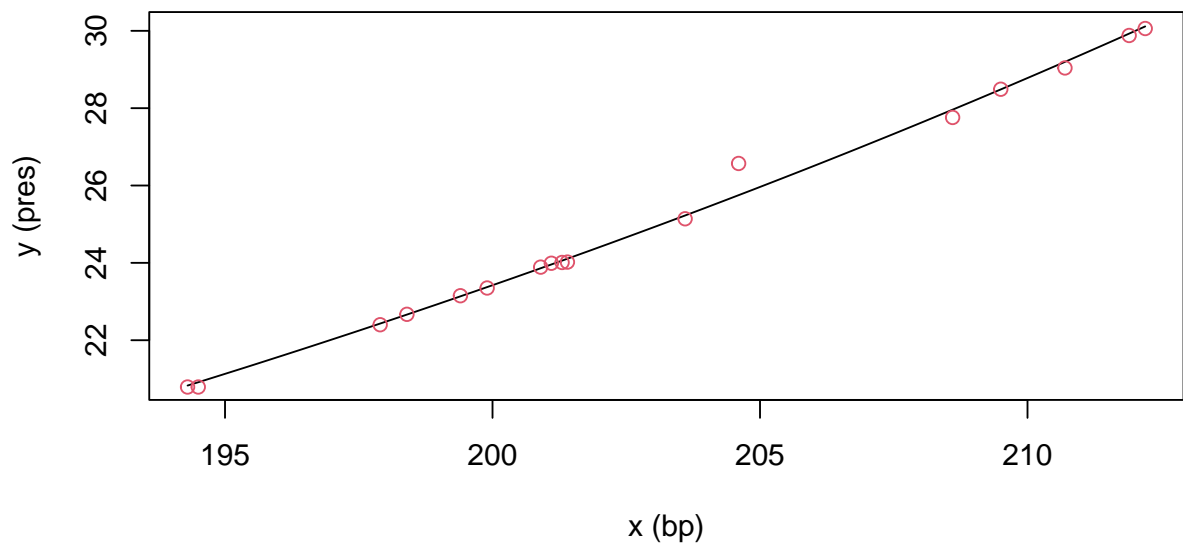
f_x <- function(x, theta){

  return((exp(theta[2]*x)*theta[1]))

}

curve(f_x(x,theta = hat_theta),min(bp),max(bp),xlab="x (bp)",ylab="y (pres)")
points(pres~bp,col=2)

```



```

# Alternative solution

hat_theta_2 = cov(bp,log(pres))/(var(bp))
hat_theta_1 = exp(mean(log(pres))-hat_theta_2*mean(bp))

curve(f_x(x,theta = hat_theta),min(bp),max(bp),xlab="x (bp)",ylab="y (pres)")
curve(f_x(x,theta = c(hat_theta_1,hat_theta_2)),min(bp),max(bp),add=T,col=2)
points(pres~bp)

```

